Use of Convolutional Neural Network for Fully Automated Segmentation of Hard Exudates in Retinal Images

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Introduction

- Purpose: describe a fully automated deep learning-based method to segment hard exudate from retinal images of patients with Diabetic Retinopathy
- Convolutional Neural Network consists of an input and an output layer, as well as hidden layers in between
- Implementation of a U-Net-based convolutional neural network (CNN) based model
- The real world applications of cutting edge machine learning techniques in the medical field

Diabetic Retinopathy (DR)

- One of the leading causes of blindness and visual impairments worldwide, especially in developing countries
- DR affects 80% of patients with diabetes and is the leading cause of blindness around the world [1]
- If Diagnosed early can be treated and prevented
- Hard exudates (HE): one type of lesion that appears as sparse yellow-white region on retinal images with the varying size
- HE was chosen since it is often the more prominent lesion type in DR patient retinas

Method

Training

Input Image

Celled Image

Filtered Image

U-Net Architecture

**Convolutional
U-Net
Hard Exudate
Model**

Input Image

Celled Image

Filtered Image

U-Net Architecture

What is the U-Net?

- Passes images through shrinking and expanding layers in order to learn patterns and features
- A convolutional network architecture for fast and precise segmentation of images

Specifics of U-Net Model

- Filter Size of 32
- Dice Coefficient = $\frac{2 * |X_1 \cap X_2|}{|X_1| + |X_2|}$
- ELU
- Data Augmentation (Rotating, Shifting)
- Batch Normalization (Reduces overfitting) [2]
- Fully Convolutional

[2] U-Net Architecture

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**Convolutional
U-Net
Hard Exudate
Model**

Testing

Input Image

Celled Image

**Convolutional
U-Net
Hard Exudate
Model**

Output Binary Mask

Output Image

Results

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Metrics Used

- True Positive/Negative, False Positive/ Negative
 - TP is a correct delineation of a lesion
 - TN is a correct delineation of a non-lesion pixel
 - FP is an incorrect delineation of a lesion pixel (is supposed to be a non lesion)
 - FN is an incorrect delineation of a non-lesion pixel (is supposed to be a lesion)

- Dice Coefficient $DICE = \frac{2 * |X_1 \cap X_2|}{|X_1| + |X_2|}$ X_1 - the auto generated matrix
 X_2 - the ground truth matrix

- Precision $PPV = \frac{TP}{TP + FP}$

- Accuracy $ACC = \frac{TP + TN}{P + N}$

- Specificity (True Negative Rate) $TNR = \frac{TN}{TN + FP}$

- Sensitivity (True Positive Rate) $TPR = \frac{TP}{TP + FN}$

Statistical Evaluation

- 26 Test Images
 - I.e. 26 retinal images that the model was not trained on and has never seen before

Metric 1: Comparing Auto Generated Mask to Ground Truth Mask

- Dice = **67.23 ± 13.60%**
- Specificity = **99.74 ± 0.35%**
- Precision = **75.87 ± 18.14%**

Metric 2: Detection Rate

- Output Masks were summed and if they were greater than a unit sum of 8500 they were designated as unhealthy and at risk
- Sensitivity (True Positive Rate) = **96.15%**
 - Meaning only 1 of the 26 images was falsely marked as healthy
- Overall Accuracy = **88.46%**
- This is the most important metric since it evaluates the models performance as it would be desired in the real world

Overall Detection Ability

Blue: Automatically
Generated Mask

Red: Ground
Truth Mask

Detecting Fine Details

Blue: Automatically
Generated Mask

Red: Ground
Truth Mask

Future Improvements

- Future improvements of the model
 - Creating a model that will be able to diagnose and classify all types of lesions that diabetic retinopathy can cause (5 types)
- Summing of the matrix can determine severity of DR
- Implementing the model into an eye scanner to give you immediate results

Conclusions

- Key technology for revolutionizing the medical industry
- High potential for growth and improvement
 - Hardware improvements benefit it greatly (decreases processing time)
 - Popularization of the technology will only further quicken its advancement
- Will benefit the economy, our lives and many more aspects of the world
 - Allowing for more patient doctor face to face time

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Questions

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